FILTERING P2P LOANS BASED ON CO-UTILE REPUTATION

Abeba Nigussie Turi, Josep Domingo-Ferrer and David Sánchez
Universitat Rovira i Virgili
Dept. of Computer Engineering and Mathematics
UNESCO Chair in Data Privacy
Av. Països Catalans 26, E-43007 Tarragona, Catalonia

ABSTRACT

Peer-to-peer loans suffer from a mistrust effect, which is amplified by the information asymmetry underlying the P2P online lending market. In this work, we assume that a reputation capital can act as a trust-building intangible collateral in such a market. We leverage a distributed reputation protocol based on the co-utility principle, whereby peer interactions should be mutually beneficial and hence self-enforcing. In this co-utile protocol, rational peers cooperate to compute each other's reputation scores. Reputation scores of borrowers are computed based on the outcome of direct transactions. Then, the reputation mechanism helps filter credible borrowers based on their respective reputation scores. By using an experiment on a simulated platform with a randomly selected sample of loans from LendingClub, we show that this protocol can improve the efficiency of the P2P online lending market by filtering out defaulting borrowers. Moreover, the results show that there is a negative correlation between the probability of default and the global reputation of the borrowers, which implies that the protocol helps accurately identify each borrower's type.

KEYWORDS

P2P Lending, Co-utility, Reputation, Trust

1. INTRODUCTION

Financial technology, also known as FinTech, is a line of business based on using software to provide financial services. FinTech companies cover a wide range of sub-industries, one of which is peer-to-peer lending. P2P lending acts as a substitute for the brokerage function of transaction banking. Some examples of P2P online lending marketplaces are: Lending Club (the world's largest P2P online lending platform), Prosper Marketplace, Funding Circle, Zopa, SoFi, Comunitae, etc. A number of reputation mechanisms have been applied to the internet-based business models. Some of these include consumer and agency- based ratings, like those of eBay, and community-based reputation mechanism in which groups of special interest signal the creditworthiness of an individual project or loan request in the crowd-based business models (Turi et al. (2016) and Collier and Hampshire (2010)). Moreover, loans are also filtered based on their characteristics, also known as financial arbitrage, which depicts their historic performance relative to the other loans of the same grade. However, these mechanisms are managed mostly centrally and, whenever handled in a distributed way, they lack a self-enforcing nature; as a result, they are exposed to tampering attacks and have a potential of being manipulated to one peer's interest. To mitigate these issues, we propose a novel way of computing the borrower's reputation in a decentralized way, accounting for all underlying loan characteristics and past records of transaction. This mechanism will make the computation self-enforcing and beneficial for all involved agents (co-utile, see Domingo-Ferrer et al., 2016).

The remainder of the paper is organized as follows: Section 2 reviews related works; in Section 3, we introduce the concept of co-utility and discuss co-utility in the P2P online lending market; Section 4 presents a distributed co-utile reputation protocol and its application to the P2P online lending market; in Section 5, we present an experimental analysis on randomly selected sample data from the LendingClub; finally, a brief conclusion and directions for future work are provided in Section 6.

ISBN: 9978-989-8533-56-2 © 2016

2. RELATED WORKS

Information asymmetry is one of the underlying factors that calls for an efficient reputation mechanism that narrows the information gap between collaborating agents. However, the nature, reliability and the dissemination mechanism of information define the efficiency of a reputation protocol to be adopted for a given network. Chen et al. (2004) compared in their experimental study different reputation mechanisms based on the level of information and self-reporting. Accordingly, they defined a trust value in a range [0, 1], where trust values of 1, 0 and 0.5 represent complete trust, distrust and uncertainty, respectively. Buskens (2002), on the other hand, argues that the number of links in a network explains why agents trust more one network than another, while the number of links of an agent explains why another agent trusts this agent more than the others in the same network. These metrics allow developing a control and learning behavior on the agents that continually interact. A number of many other authors have suggested a mechanism for building trust in a given network (ranging from Kamvar et al. (2003), to Collier and Hampshire (2010) and Donato et al. (2007)). More recent work by Domingo-Ferrer et al. (2016) suggests a distributed and co-utile way of computing the agents' reputation. This mechanism has the attractive properties of being attack-tolerant, anonymous, cost-effective and computed in a self-enforcing decentralized way. In this paper, we adapt this mechanism to the P2P online lending market, which is seriously prone to the mistrust effect.

3. CO-UTILITY IN THE P2P ONLINE LENDING MARKET

Co-utility refers to self-enforcing and mutually beneficial interaction among self-interested agents (Domingo-Ferrer et al., 2016). Given a game in extensive form, a protocol refers to either a path from the root to a leaf or a subtree from the root to several leaves implying a sequence of actions chosen by players. For instance, a business model of the P2P online lending market or a specific strategic behavior of the borrowers and lenders in the market and their respective sequence of interactions implies the protocol of this game. A protocol designed in a way to be self-enforcing and mutually beneficial for the involved agents guarantees co-utility in the game. Co-utility can naturally arise, or it can be induced through artificial incentives in case a protocol is not naturally co-utile. Let us formally define self-enforcement and co-utility in protocols.

Def. 1 (*Self-enforcing protocol*): A protocol is self-enforcing if, at each successive node in the protocol path, sticking to the next action prescribed by the protocol (taking the next edge in the path) is an equilibrium of the remaining subgame (the subtree rooted at the current node), that is, a subgame perfect equilibrium of the game.

Def. 2 (*Co-utility*): A protocol *P* on a game *G* is co-utile if: i) it is self-enforcing; ii) the utility derived by each agent participating in *P* is strictly greater than the utility the agent would derive from not participating; and iii) *P* is Pareto-optimal (i.e., there is no alternative protocol *P'* on *G* giving greater utilities to all agents and a strictly greater utility to at least one agent).

P2P online lending is an example of a co-utility amenable game. The borrower's utility function can be defined as: $U_b = U\left(y + \delta(t)\left(l_0 - P.\frac{1-(1+i)^{-n}}{i}\right)\right)$, where y is the borrower's income, $\frac{1-(1+i)^{-n}}{i}$ is the present value of a loan amount l_0 with future annuity payments, P, n number of terms of the loan and a random interest rate i; $\delta(t)\epsilon[0,1]$ is a weight parameter for the level of impatience of the borrower to get the loan at a given time t. $\delta(t)$ values close to 1 imply higher patience level. A rational borrower makes a loan request that maximizes her utility. On the other hand, there are two types of lenders in the P2P lending: pure lenders that lay on their own capital for investing in the P2P lending and lenders with re-investment, those who partially or wholly rely on a borrowed capital for re-investing in the same network in order to make profit through arbitrage opportunities in the market (*P2P loan carry trade*). The expected utility function for the pure lender with a loan amount l_0 is given as $u_l = \sum_{n=1}^{n} u[(i-r)l_0\gamma(t)p(t)]$, where i and r are the nominal and real market interest rates, respectively, $\gamma(t)$ is the proportion of the loan paid at time t over the loan period n and $p(t)$ is the probability of default at time t.The utility function of the borrower with a re-investable borrowing is defined as $u_l{}' = u\left(\frac{rL-r'(L-K)}{K} - \frac{\delta^2(\Pi)}{2\beta}\left(\frac{L}{K}\right)^2\right)$, where K is the borrower's investable capital, L is the loan amount, and r and r' are the random lending and borrowing interest rates, respectively.

The lender makes a profit from the spread between r and r'. The utility maximization problem of the lender with a re-investment motive depends on the difference between the total return on the loans, $\frac{rL-r'(L-K)}{K}$, and the total funding cost (total risk), which is the product of the risk on the loans, $\delta^2(\Pi)$ and the lenders' leverage, $\left(\frac{L}{K}\right)^2$. The market commonly operates with a large anonymous crowd in which there is information asymmetry between peers. As a result, there exists a mistrust effect which reduce its efficiency deviating the market to an unintended outcome and making it not co-utile. In order to elaborate this, consider a binary trust game presented in Fig 1. A lender (A) and borrower (B) have \$10 each. A's decision to lend money to B depends on her trust level on B, and B's decision to payback depends on her trustworthiness.

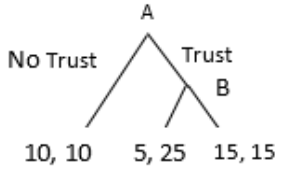


Figure 1. A Binary Trust Game

The Nash equilibrium of this game is (10, 10); no flow of money. With a full trust, any return by the borrower greater or equal to \$10 implies a Pareto optimal situation in which none of them could be made better off without making the other worse off. Hence, based on Definition 2, this game is not co-utile. Therefore, making this transaction to be co-utile requires an efficient and self-enforcing incentive scheme, one of which is a reputation mechanism that guarantees trust between agents.

4. DECENTRALIZED CO-UTILE REPUTATION MECHANISM FOR A P2P ONLINE LENDING MARKET

4.1 Decentralized Co-utile Reputation Mechanism

The decentralized co-utile reputation mechanism we use is an extension to the well-known EigenTrust mechanism (Kamvar, et al., 2003), with additional properties of being fully distributed and co-utile (and, thus, self-enforcing) (Domingo-Ferrer et al., 2016b). Being decentralized, it helps avoid interference by any central authority to compute reputations and hence reduce the problems of biased computation and privacy issues arising from computation by a sole central entity. The protocol also has additional interesting features that make it relevant for P2P lending. Specifically, agents computing each other's reputation in a distributed way remain anonymous to each other during the calculation process. In addition, it is cost-effective with a limit on the number of messages and communication iterations needed to compute reputations and, being an outcome-based computation, its computation can run parallel to the main P2P transaction. This protocol also manages new agents by assigning them zero reputation scores as if they were malicious agents, thereby disincentivizing the creation of new or multiple identities to "clean" malicious past behaviors. The protocol computes global reputation scores of agents based on local reputations resulting from individual transactions.

Local reputation refers to the reputation score (trust) of an individual target agent j, computed by another agent i, who had a direct transaction with j. The local reputation is defined as the summation of payoffs (reward/loss) resulting from the set of transactions, Y_{ij}, of i with j:

$$s_{ij} = \sum_{y_{ij} \in Y_{ij}} payoff_i(y_{ij}). \qquad (1)$$

The *global reputation* of an agent j, is the aggregation of each local reputation value s_{ij} computed by the agents who directly interacted with j. In order to compute this value, first, each local reputation value is normalized to a value between [0, 1], which gives positive values for well-behaved agents and zero for both ill-behaved agents and newcomers:

$$c_{ij} = \frac{\max(s_{ij}, 0)}{\sum_j \max(s_{ij}, 0)}. \qquad (2)$$

This normalization helps prevent agents from whitewashing a bad reputation (i.e., to operate with a new pseudonym or start all over) and instead creates an incentive for building and maintaining one's own reputation. The normalization also guarantees that all agents contribute equally to the computation of global reputations, regardless of the number of transactions.

To compute global reputation values, the normalized local reputation values are aggregated based on the notion of transitive trust. By transitive trust, we mean that, if agent i trusts any other agent j, then she trusts all other agents trusted by j. Therefore, the global reputation value of agent k, g_{ik}, is computed by taking the local reputation values of k from other agents j who have directly interacted with an agent k, and weighting the values with the respective local reputation value agent i has assigned to agents j. Hence, the estimated global reputation of k is given by $\hat{g}_{ik} = \sum_j c_{ij} c_{jk}$. The co-utile nature of the protocol lies in that the global reputation of each agent k is computed by one or several other agents (called score managers of k) on behalf of k, which themselves are participating peers in the same network. If the score manager knows c_{ij} for the whole network, the entries generate a matrix of local reputation values, $C = \{c_{ij}\}$. The matrix construction assigns zero entries for those agents with no interaction. Consider the vector $\bar{c}_i = (c_{i1}, ..., c_{in})^T$. Then, every agent i can compute $g_i^m = (C^T)^m \bar{c}_i$ for $m = 1,2, ...$ If C is irreducible and aperiodic, as m grows, g_i^m converges to a vector g that is identical no matter which agent computes it. This vector is the left eigenvector of C and its components are the global reputations of agents.

According to the implementation of the protocol in Domingo-Ferrer et al. (2016b), the score managers that compute an individual agent's global reputation are defined according to a distributed hash table (DHT) associated with the network topology, which maps each agent to a set of several score managers. The system works in such a way that every agent i is a score manager of another set of agents (daughter agents, D_i, w.r.t. this score manager), and has its own score manager itself, thus fairly balancing the load of reputation calculations. Computation of the global reputation for an agent k (a daughter agent of agent i) is based on the local reputation of k w.r.t. the set of agents, J, with whom agent k had direct interaction, weighted by the reputation of these agents w.r.t. their score managers. This guarantees the computation to be handled in a distributed way without any individual agent's direct influence. Note that the local reputation of an agent $j \in J$ with respect to agent i is $c_{ij} = 0$ for $j \notin A_i$, where A_i is the set of agents with whom an agent i had direct interaction. A simplified computation a lending transaction is presented in Figure 2 in which a score manager i computes the global reputation score of a single borrower k). The figure depicts a graph with local-trust-value weighted nodes of a network of interaction of peer k. The computation of k´s global reputation by a single score manager, SM_k is based on their network of interaction.

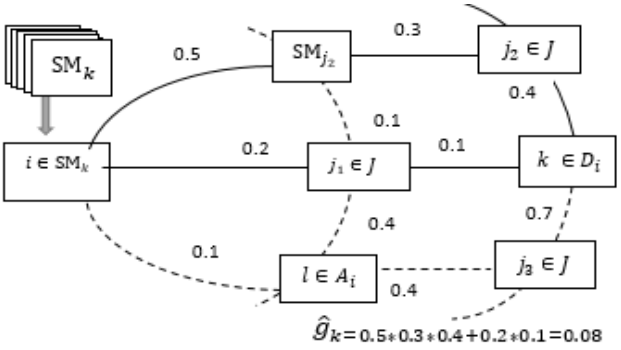


Figure 2. Co-utile reputation calculation (SM_k and SM_{j_2} are the score managers of k and j_2 respectively)

4.2 Application to the P2P Online Lending

Now let us define the local and global reputation of a borrower in the P2P lending scenario. Given a direct transaction set, Y_{ij}, between borrower j and lender i, the local reputation of a target borrower j, with respect to i is the aggregate payoffs (net return) that i has obtained from this set of transactions. Based on Equation (1) above, the local reputation of an individual borrower with a loan type τ is the summation of the utilities derived by lender i from a set Y_{ij}:

$$S_{ij} = \sum_{y \in Yij} u(x)_{iy}, \qquad (3)$$

where $u(x)_{iy}$ is the utility of investor i in the transaction y from the set of transactions Y_{ij}, performed with a borrower j. This measures the degree of satisfaction/dissatisfaction obtained after the analysis of the transaction outcome. For uniformity of the analysis of the various satisfaction measures, we bound the range of values of this utility function within [-1, +1]. Hence, agents give values close to -1 to defaulters and values close to +1 to reflect satisfaction (honesty of the target agent), as follows:

$$u(x)_{iy} = 1 - {}^{2}/_{(1+\exp(x))} \qquad (4),$$

where x is the net return on investment, $x = (1 - \mathrm{p(t)}_j^{\tau})c_i(1+r) - \mathrm{p(t)}_j^{\tau}c_i$, such that c_i is the initial investment and r is the random interest rate, including the risk premium, and $\mathrm{p(t)}_j^{\tau}$ is the conditional probability of default for the borrower j at time t over the loan period T, and it depends on the loan characteristics τ. Note that the probability of default is private to the individual borrower and is realized ex-post. This probability can be estimated using the Cox proportional hazard model (David, 1972), $\mathrm{p(t)}_j^{\tau} = p(t)0e\beta X$, where $pt0$ is the baseline hazard function implying the risk of default for the loans whose covariates X (filtering characteristic variables) are all assumed to be zero. It shows the probability of default of a hypothetically average loan, without any loan characteristic effect. On the other hand, the effect parameters show how the probability of default varies depending on loan characteristic covariates X. The model implies that the covariates play a multiplying effect on the baseline hazard function in defining the creditworthiness of the loan. The main characteristics of the loan that can be drawn from the available set of data provided on the credit details of the borrowers on the platforms include: Rating/Grade, Loan Amount, Debt-to-Income ratio, Credit Lines, Number of Delinquencies, Inquiries in the past 6 months, Length of Employment, Home Ownership, Loan Purpose, Number of Public Records, Borrower's Age (active, on retirement), and Term of the Loan. This set of loan characteristic indices is used by individual investors in basic filtering and third-party automated algorithmic investment filtering.

Based on Equation (2), the normalized local reputation value for a potentially non-defaulting borrower is positive, and zero otherwise (i.e. in the case of defaulting or just being a newcomer to the market with no reputation). New entrants can be filtered out with the underlying zero reputation score and loans with higher risk are already priced at a higher interest rate. Hence, the normalization incentivizes new borrowers to have a positive reputation in order to distinguish themselves from ill-reputed borrowers. This implies that positive normalized reputation values signify honesty at a local level. A matrix of local reputation values, C, will have zero entries for those borrowers and lenders with no interaction. In addition, a small positive reputation score is assigned to the lenders, where they are assumed to be relatively credible with regard to this specific transaction as a lender. Hence, we set this reputation value to be $1/n$, where n is the number of players in the network. This is reasonable, as the level of targeted connection and trust between 2 persons in the lower extreme is better than the level between 1000 people (Buskens (2002)).

By referring to the global reputation of a borrower, any potential lender decides whether to lend money to this borrower. If there exists a past record of a transaction between the two, the lender can also consider the local reputation she assigned for this borrower. In the cases where the global and local reputation scores are different, the lender makes a decision on collaboration with this borrower based on the relatively lower value.

5. EXPERIMENTS

To evaluate the effect of reputation management in P2P lending, where investment decisions are made merely based on the platform-based filtering, we took a sample network of 200 lenders and borrowers. During each round of transactions, we assumed that each borrower could borrow at most once, while each lender could invest in as many notes as she could afford and was willing to invest in this market. The data for this analysis was sourced from the LendingClub Statistics[1], where a random sample of 200 loans with an average probability of default of 0.085 was taken. Note that this simulation is a simplistic presentation of the scenario and the probabilities drawn in it were on random bases, and did not take into account the underlying loan characteristics. Here, we used a right-skewed beta distribution (in order to get normally distributed

[1] https://www.lendingclub.com/info/statistics.action retrieved on 28/6/2016

values in the range between 0 and 1), where the mean of the beta distribution was given by $1/(1+\frac{\beta}{\alpha})$. Hence, given an average probability of default of 0.085, with $\alpha = 5$ and, hence, $\beta = 53.824$, the beta distribution generated random probability values of interest with an average probability of default as in the sample data. The minimum and maximum loan amount in this sample were \$1,000 and \$35,000, respectively, with an average loan request amount of \$15,095.75. The loans were composed of either 36 or 60 terms. The goal of this computation is to derive the global reputation of borrowers based on the payoff which lenders derive from each of them and individual successive lending transactions. By using Equation (4) above, we computed the utility derived from investing in this P2P lending network and, based on this, the local reputation of each individual borrower and lender (for those borrowers who also borrow for re-investment purpose). The utility values computed based on this formula were used to calculate the respective local reputation score of each borrower in the market. The size of the network was 200, with 100 lenders and 100 borrowers, and we set a fixed positive reputation score of 0.01 for the lenders. Note that, based on the EigenTrust rule of computation, entries in the normalized local reputation for those agents with no interaction (borrower-to-borrower here) are set to zero. In the first iteration, we took an initial reputation vector of size 200×1 with 0.01 entries for the lenders and 0 entries for the borrowers (which accounts for the reputations prior to these transactions) and this vector was multiplied by the transpose of the local reputation score matrix. The successive global reputation score was based on each preceding global reputation. We repeated this step until the factor between the successive global reputation scores of each borrower was less than 10^{-5} (i.e. $\delta_i < error$). The computation is simulated for two main lending market scenarios:

(1) *Lenders cannot borrow.* Based on the underlying pre-trusted peer assumption of the reputation protocol, the initial reputation for lenders is set to a small positive value (0.01), to avert the problem of zero reputation for a lender that earns no reputation as a borrower.

(2) *Lenders can borrow.* In this case, the *mistrust effect* is multidirectional in that any potential lender can be in the position of a borrower. To use the transitive trust assumption, the local reputation assigned by a lender needs to be weighted by the reputation the lender earns as a borrower.

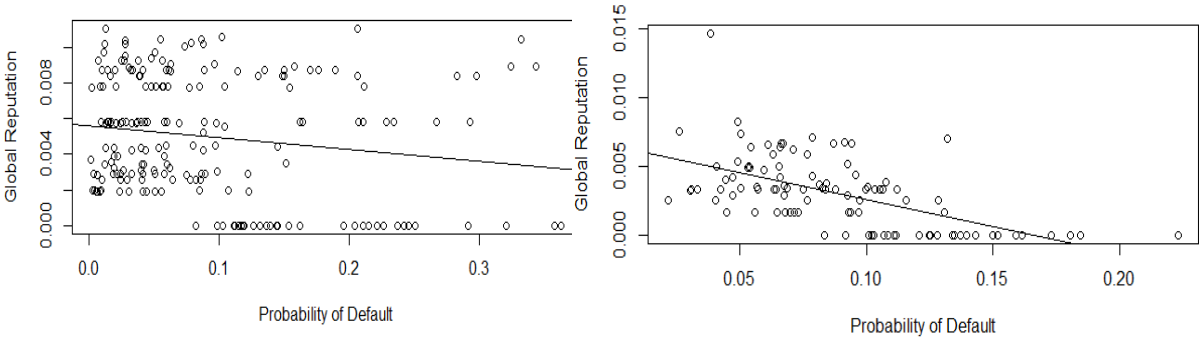


Figure 3. Global reputation scores vs. probability of default for pure borrowers; 1st-round (left) and 100 successive transactions (right). Pearson's product-moment correlation 95% CI: -0.17 (left) and -0.59 (right)

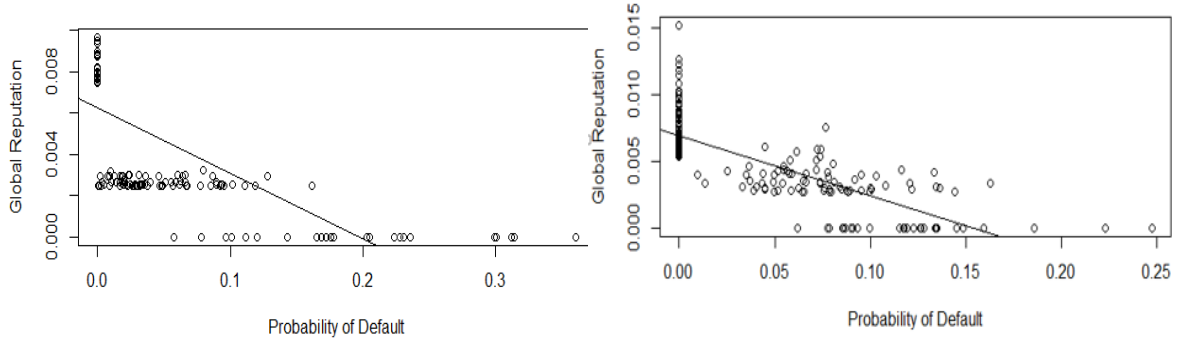


Figure 4. Global reputation vs. probability of default with re-investment; 1st-round transaction (left) and 100 successive transactions (right). Pearson's product-moment correlation 95% CI: -0.71 (left) and 0.78 (right)

Furthermore, in order to see the evolution of global reputation in the long term, we considered further computations with more than one transaction. For instance, a randomly selected borrower with a probability of default of 0.01 (which is internally perceived by the borrower and is fixed for each transaction) implies that this borrower will default at least once in 100 repeated transactions. The reputation protocol should be able to capture the behavior of this borrower by refining the computation according to the type of borrower in each lending transaction. Hence, to this end, we repeated transactions 100 times. The results are presented in Figs. 3 and 4, respectively for pure lenders and for lenders that can borrow. The protocol identified ill-behaved borrowers by assigning low global reputation scores as the computation gets refined in successive iterations. Hence, with repeated transactions over time, the global reputations will highly be correlated with the probability of default. The fitted line in the figures depicts a negative correlation between reputation and probability of default of the borrowers, ceteris paribus. The Pearson's correlation test for the plots above shows that there is a statistically significant negative correlation between the global reputation and probability of default, with an increasingly strong correlation through successively repeated transactions of 100 times. Figure 3, shows a downhill linear relationship between the global reputation and the probability of default that is stronger after 100 transactions (-0.59 correlation coefficient) as reputations build up through successive transactions. Figure 4 shows analogous results for the re-investment case. Therefore, by examining global reputations in the long term, lenders can filter borrowers according to their probability of default.

5.1 Filtering Credible Borrowers

In order to collaborate with the loan request of borrowers in the network, lenders filter loans based on a minimum global reputation score according to their risk preference. Here, a quite important thing to consider is the question of how the system acts with the minimum threshold of global reputations set by the potential lenders for any collaborative decision. With the assumption of pre-trusted peers underlying this reputation protocol, borrowers with re-investment motive tend to have relatively higher reputation scores than pure borrowers. Besides, there also is a spillover effect of the borrowers' credibility on the reputation of those lenders who partially lay on the capital sourced from this network. Hence, the more risk-averse the lenders in the network, the higher the minimum threshold of global reputation, and as a result, the higher the number of loan requests to be filtered out.

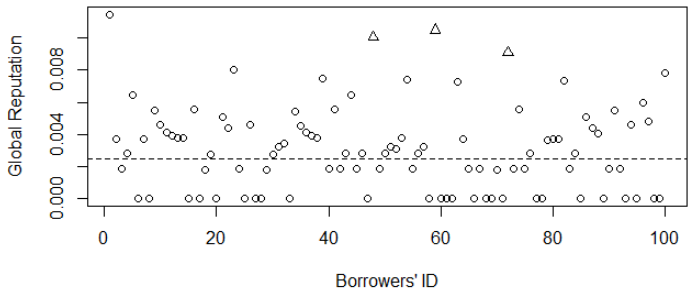


Figure 5. Global reputation scores of each borrower in the network: deterministic vs. probabilistic loan filtering

In Figure 5 above, the horizontal dashed line represents the threshold global reputation ($\bar{g}_i$=0.0025) based on a deterministic approach. This approach requires a standardized level of global reputation, which every borrower needs to minimally attain accounting for all loan characteristics. The extreme case is to pick a borrower with the highest reputation score. If a probabilistic algorithm is employed, given a vector of global reputation $g = \{g_1, g_1, .. g_n\}$, a potential lender chooses an honest borrower $i(g_i>0)$ with probability $\frac{g_i}{\sum_{j=0}^{n} g_j}$ and chooses a dishonest borrower j (g_j=0) with a fixed probability of 0.1 (fairly accounting for newcomers; see Kamvar, et al. (2003)). Presented in a simplistic way, in Figure 5, the triangular points in the plot represent the three consecutively selected borrowers with high reputation based on the $\frac{g_i}{\sum_{j=0}^{n} g_j}$ condition, where $\sum_{j=0}^{n} g_j = 1$; borrowers with larger reputation score, g_i will have a higher chance to be selected as compared to the others with low g_i. Since P2P loans have no collateral, we assume that *reputation capital* (reputation of the borrower) is an intangible collateral of this transaction. Borrower k defaults if the value of defaulting $v^d(c_i, \bar{g}, g_k))$ is greater than the value of paying back, $(v^p(R) = c_i(1 + r)$. Her gain from the

default is the loan amount originated, given an initial presumed small positive reputation of the system, $\bar{g}$. Yet, with the current transaction's default, she will also lose her reputation g_k. Hence, $v^d(c_i, \bar{g}, g_k, f_o) = c_i - f_o - \bar{g} - g_k$, where f_o is the origination fee (commonly 5% of the loan). This also implies that reputation gain punishes an intention to default. In order to standardize the computation together with the global reputation scores, the loan amount and return to the lender are normalized to be between 0 and 1. Therefore, given the global reputation scores, a potential lender will reject the loan request by borrower k if $v^d(c_i, \bar{g}, g_k) > v^p(R)$.

6. CONCLUSION

In this paper, we enforce trust in the P2P online lending market by means of a (co-utile) reputation management protocol. The local and global reputation scores of borrowers in the market are computed based on the notion of transitive trust underlying the protocol. The mechanism helps mitigate the mistrust problem underlying the market and is a complement of the existing loan filtering mechanism. Despite its interesting features, this reputation mechanism has two main limitations; (1) it is purely outcome-based and (2) it does not consider the prior reputation of newcomers, but assigns them zero reputation scores with the purpose of discouraging strategic whitewashing. A future work direction is to develop an aggregated decentralized co-utile reputation that takes into account transactional outcome-based reputation, social reputation (which can be sourced from the social network/media of the borrowers) and other market-related reputations of borrowers with proper weights for each reputation type. A second direction for future work could be to set a standardized threshold level of 'honest reputation', which can come from an analysis of the dynamics of the system under various minimum levels of reputation score in line with the lenders' level of risk tolerance.

ACKNOWLEDGEMENT

Funding by the Templeton World Charity Foundation (grant TWCF0095/AB60 "CO-UTILITY") is gratefully acknowledged. Also, partial support to this work has been received from the Government of Catalonia (ICREA Acadèmia Prize to J. Domingo-Ferrer and grant 2014 SGR 537), the Spanish Government (project TIN2014-57364-C2-1-R "SmartGlacis") and the European Commission (project H2020-644024 "CLARUS"). The authors are with the UNESCO Chair in Data Privacy, but the views in this paper are the authors' own and are not necessarily shared by UNESCO.

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